# Super Resolution approach using Generative Adversarial Network models for improving Satellite Image Resolution

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**Abstract.** Recently, the number of satellite imaging sensors deployed in space has experienced a considerable increase, but most of these sensors provide low spatial resolution images, and only a small proportion contribute with images at higher resolutions. This work proposes an alternative to improve the spatial resolution of Landsat-8 images to the reference of Sentinel-2 images, by applying a Super Resolution (SR) approach based on the use of Generative Adversarial Network (GAN) models for image processing, as an alternative to traditional methods to achieve higher resolution images, hence, remote sensing applications could take advantage of this new information and improve its outcomes. We used two datasets to train and validate our approach, the first composed by images from the DIV2K open access dataset and the second by images from Sentinel-2 satellite. The experimental results are based on the comparison of the similarity between the Landsat-8 images obtained by the super resolution processing by our approach (for both datasets), against its corresponding reference from Sentinel-2 satellite image, computing the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity (SSIM) as metrics for this purpose. In addition, we present a visual report in order to compare the performance of each trained model, analysis that shows interesting improvements of the resolution of Landsat-8 satellite images.

**Keywords:** Super Resolution · SR-GAN · Landsat-8· Sentinel-2.

## 1 Introduction

According to [1], currently, there is an increasing demand for obtaining high resolution images, so the applications in different research areas, such as computer vision, remote sensing, medical, among others, could take advantage of the quality of that type information and be able to improve its results; however, this particular scenario (of working with high resolution images) can not always be ensured, and that is the case of remote sensing applications, in which, huge amounts of information (images) provided by the satellites around the Earth is provided, but only a few proportion of that images are available at higher resolutions. One way to overcome this problem is through the applications of digital image processing techniques, such as Super Resolution (SR), which is the process of generating high resolution (HR) images from low resolution (LR) images [16].

Classic models of SR techniques use linear, cubic splines, lanczos, filtering, among other approaches, as interpolation methods to improve image resolution; but these techniques have major problems in processing the fine details in the images, such as those representing curves, edges and abrupt intensity variations between neighboring pixels [2]. As an alternative, these classical methods can be replaced by models based on deep learning approaches [3], [4], [5]; however, there is still a problem when dealing with complex textures. According to [6], those problems can be solved by performing the SR process using a Generative Adversarial Network (GAN) combined with convolutional networks (hereafter referred as SR-GAN), so the textures or complex details in the image can be likewise improved.

In this work we replicated the methodology proposed at [6]. This work is a first approximation in the use of this type of techniques in the improvement of the resolution of satellite images of low resolution. so we could exploit the large volume of images currently available in the dataset used in that work. We used that model as baseline to train our specific model, adjusting it with Sentinel-2 satellite images, so these technique, SR-GAN, could be used to improve the low resolution of Landsat-8 satellite images for its use in different remote sensing applications. For this purpose, we have created a new and different datasets for training and validating the model to improve Landsat-8 satellite images towards its reference provided by the Sentinel-2 satellite images.

The remaining of this work is organized as follows, the creation and preprocessing of the dataset is described in Section 2; the experimental design and the results are presented in Section 3; finally, conclusions and guidelines for future research in this area are discussed in Section 4.

## 2 Methodology

The following sub sections discuss the methodology proposed for preprocessing the images used in this work, from DIVerse2k dataset and Sentinel-2 images; in addition, a briefly description of the deep learning model architecture is also presented.

### 2.1 Dataset

**DIVerse2k Dataset** (DIV2K) is conformed by a large diversity of high resolution images collected from Internet [10], all the images are 2K resolution, that is, they have 2K pixels on at least one of its axes (vertical or horizontal), the images are of high quality in the terms of small amounts of noise. High resolution images help in classification or segmentation processes to extract information from these images, as in the cases of deforestation, land use, urban growth, natural disasters. For our work, we used 900 images of different contents. The network implementation, used for improving the satellite images resolution with the SR technique, was trained using 800 images for training and 100 images for validation.

**Sentinel2-512 Dataset** Sentinel-2 is a European mission, consisting of two twin satellites, each carrying a Multi-Spectral Instrument (MSI). Each satellite passes the same zone every 10 days [7]. Sentinel-2 is in a low 290 Km orbit, its optical instruments consist of 13 spectral bands, 4 bands with 10 meters of resolution, 6 bands with 20 m resolution and 3 bands with 60 m of resolution, providing images covering 100 Km x 100 Km [7]. For this work we used bands 2, 3 and 4, with 10 m resolution each.

For creating the Sentinel2-512 dataset, we obtained 24 images from Sentinel-2 satellite, corresponding to period from December 2018 to March 2019, those images were processed to generate the Sentinel2-512 dataset. The bands 2, 3 and 4 of each Multi-Spectral satellite image were extracted and joined into a new multichannel image with 10980 x 10980 pixel resolution. Each new image were divided in 43 tiles of 512 x 512 pixels, 21 tiles of 228 x 288 pixels, 21 of 228 x 512 pixels and 1 of 228 x 228 pixels, providing a total of 484 tiles per image. We discarded tiles with the presence of clouds and tiles with missing information (as those belonging to the extremes of the satellite image), remaining 2192 images, and we used 2000 images for training our model, and the rest for validating it.

For testing the performance of our model, when applied in a real problem, we use a Landsat-8 satellite image. Landsat-8 is part of a global research program known as NASA's Science Mission Directorate, with an orbit of 705 km at the equator, it passes the same zone every 16 days [12]. Landsat-8 is composed of nine shortwave spectral bands, 8 bands at 30 m and 1 band at 15 m of resolution. For this work, we used bands 2, 3 and 4, each at 30 m resolution.

### 2.2 SR-GAN approach

As previously introduced, Super Resolution (SR) is the process of generating high resolution (HR) images from low resolution (LR) images. Since the last three decades many techniques have been proposed for performing SR processes [15] [14]. More recently, Jianchao Yang [14] explore diverse SR techniques such as image observation models, processing at frequency domain, interpolation-restoration by non-iterative approaches, until statistical approaches. Currently, as an alternative, these classical SR methods can be replaced by models based on deep learning approaches, such as Generative adversarial network (GAN).

GAN was introduced by Ian Goodfellow [11], it proposes a new framework for estimating generative models via an adversarial process, in which two models are simultaneously trained: a generative model "G", that captures the data distribution, and a discriminative model "D", that estimates the probability that a sample belongs to the training data rather than a sample provided by G. The training procedure for G is to maximize the probability of D making a mistake.

Super Resolution techniques using Generative Adversarial Network models (SR-GAN) are based on the work of [6] and implemented by [8]. The architecture proposed by [6] is shown in the figure 1. This architecture uses two convolutional layers in the generator with 3 x 3 small kernels, 64 feature maps, followed by batch-normalization layers and a Parametric ReLU as activation function. Finally, the model increase the resolution of the input image applying 2 convolutional sub-pixel layers.

After performing the generative process, the discriminator process is applied to discriminate the images obtained from the generator. In the discriminator this architecture uses Leaky ReLU as an activation function and avoids the max-pooling throughout the network. The network contains 8 convolutional layers with an expanded number of 3 x 3 filter kernels, increasing by a factor of 2 from 64 to 512 kernels as a VGG network. The resulting 512 feature maps, then are processed by two dense layers and a final sigmoid activation function.

As presented in figure 1, for the SR-GAN architecture, the objective of the discriminator D is to discriminate if the ISR image produced by the generator G is a high resolution image, to achieve this the discriminator D is trained with the IHR images at high resolutions. The objective of the generator G is to obtain a satellite image at super resolution (ISR), based on an input image at low resolution (ILR).

## 3 Experiments and Results

This section describes the experiments that have been conducted and the results that were obtained. This work proposed to apply the SR-GAN models for processing Landsat-8 satellite images in order to increase its resolution, using two different deep learning networks for that purpose, one trained with high resolution satellite images from Sentinel2-512 dataset, and the other trained with common images from DIV2K dataset.

In this work the model proposed by [6] and implemented by [8] was replicated as the base model and proof of concept. The training was performed using and NVIDIA TITAN XP GPU.

The training of the network using both datasets, the Div2K and Sentinel2-512 , was performed using a batch size of 128 with 100 epochs and a scaling factor of 4. On the trained network, we use a Landsat-8 satellite image as input in order to assess the performance of each approach.

To evaluate the quality of our results, we use the PSNR and SSIM metrics for assessing the quality of the super resolution images. For PSNR metric, it value approaches infinity as the Mean Square Error (MSE) approaches zero; this shows that higher PSNR values defines higher image qualities. Correspondingly, a small value of PSNR implies higher numerical MSE values, defining higher

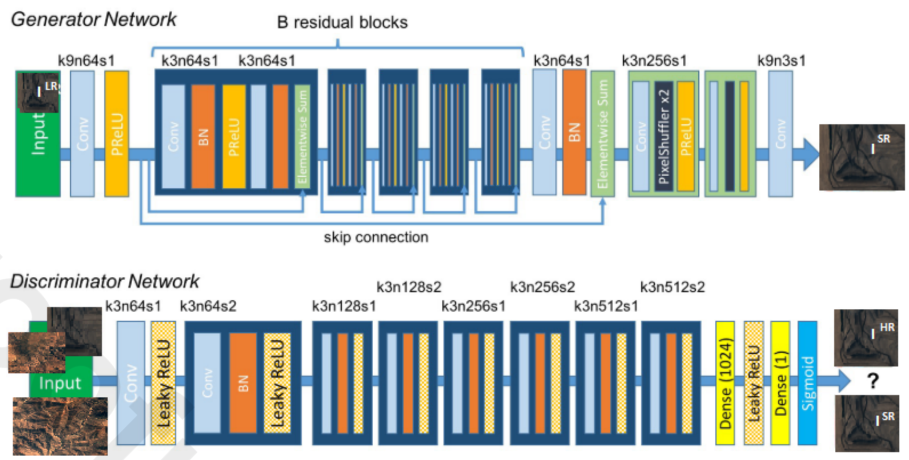


**Fig. 1.** Generator and discriminator models at the SR-GAN architecture, adapted of Ledig, kernel size(k), number of feature map (n), stride (s)

differences between images. The SSIM is a well-known quality metric used to measure the similarity between two images; possible values of the SSIM index are in [0,1] range. A value of 0 means no correlation between images and 1 means that images are similar [13].

At the training stage, the SR-GAN results were analyzed by comparing the outcomes from the models trained with the two datasets, using the PSNR and SSIM as metric for its evaluation at each epoch, the results are shown in figure 2. At the validation stage, the results are summarized in the table 1, and are those related to the comparison between the Sentinel-2 image against the two outcomes from the SR-GAN models processing a Landsat-8 image. we had a better result with the dataset Sentinel2-512.

| | **Sentinel2-512** | **DIV2k** |
|---|---|---|
| **PSNR** | 29.391 | 24.149 |
| **SSIM** | 0.803 | 0.749 |

**Table 1.** Testing results with the SR-GAN models when processing a Landsat-8 image

From a visual analysis, the images presented in figure 3 shows a tile of a Landsat-8 and a Sentinel-2 images, from the Northern Coast of Piura, in Peru; and the results obtained by processing the Landsat-8 image with both approaches

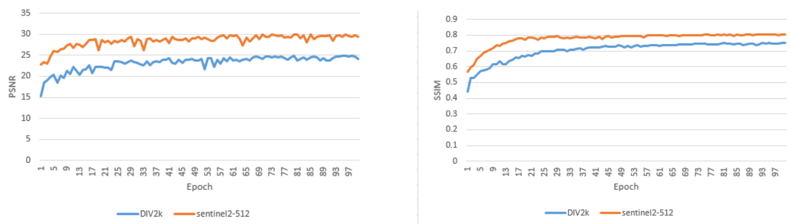


**Fig. 2.** PSNR and SSIM metrics at the SR-GAN models training stage using DIV2K and Sentinel2-512 datasets

of the SR-GAN trained models. As it can be seen in the figure, both trained SR-GAN models achieved an increase in its resolution with respect to the original input image of the Landsat-8 satellite, with a very similar approach to the Sentinel2 image.

## 4 Conclusions

This works shows that the application of Super Resolution techniques based on Generative Adversarial Network models (SR-GAN) in the improvement of the resolution of Landsat-8 satellite images is indeed possible; however we believe that this results can be improved by using 16 bit images in Tiff format. In terms of architecture as future work, the use of recent pre-trained networks, satellite images at higher resolutions, and the use of panchromatic images, could lead to a greater improvement of the resolution of Landsat-8 images. This work open lines of application, which not only serve to improve the resolution of the images of the visible spectrum of LANDSAT, but for all its bands, and even extend these approaches to images of different nature such as SAR

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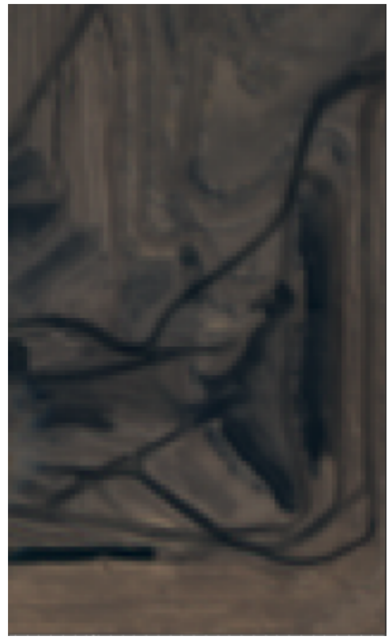
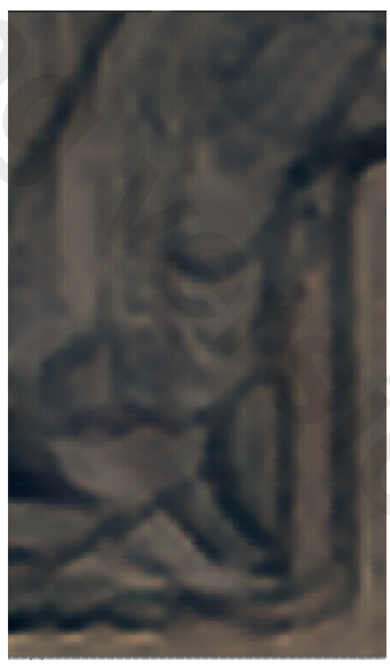
(a) Landsat-8 image



(b) Sentinel-2 image

(c) SR Landsat-8 - DIV2K



(d) SR Landsat-8 - Sentinel2-512

**Fig. 3.** Super Resolution results obtained from trainning of dataset DIV2K and sentinel2-512

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